# Artificial Intelligence of Things Wearable System for Cardiac Disease Detection

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***Abstract*—This study proposes an artificial intelligence of things (AIoT) system for electrocardiogram (ECG) analysis and cardiac disease detection. The system includes a front-end IoT-based hardware, a user interface on smart device's application (APP), a cloud database, and an AI platform for cardiac disease detection. The front-end IoT-based hardware, a wearable ECG patch that includes an analog front-end circuit and a Bluetooth module, can detect ECG signals. The APP on smart devices can not only display users' real-time ECG signals but also label unusual signals instantly and reach real-time disease detection. These ECG signals will be uploaded to the cloud database. The cloud database is used to store each user's ECG signals, which forms a big-data database for AI algorithm to detect cardiac disease. The algorithm proposed by this study is based on convolutional neural network and the average accuracy is 94.96%. The ECG dataset applied in this study is collected from patients in Tainan Hospital, Ministry of Health and Welfare. Moreover, signal verification was also performed by a cardiologist.**

***Keywords*—Arrhythmia, atrial fibrillation, convolutional neural network, electrocardiogram, artificial intelligence of things, wearable device, application, cloud server.***

## I. INTRODUCTION (*HEADING 1*)

Arrhythmia is a leading cause of heart disorder. It can be divided into three categories: premature heartbeat, tachycardia, and bradycardia. Although most arrhythmias do not present immediate risk and usually happen in our daily life, atrial fibrillation is the main cause of acute stroke, and ventricular tachycardia is the leading cause of shock or sudden cardiac death.

According to statistics from the World Health Organization [1], approximately 15% of deaths are due to arrhythmias worldwide. Meanwhile, approximately 80% of sudden deaths are caused by cardiovascular diseases. Arrhythmia is the most significant cause of death for those with cardiovascular diseases. There will be approximately 12 and 17.9 million people who will suffer from atrial fibrillation in the USA in 2050 and Europe in 2060, respectively [2]. For the sake of daily health care in an aged society, if users can attach a wearable monitoring device, which can detect unusual electrocardiogram (ECG) signals and instantly send a warning message to the hospital, this device will prevent many tragedies from happening.

This study focuses on several common arrhythmias and builds a convolutional neural network (CNN)-based algorithm for cardiac disease classification. Moreover, an Internet of things (IoT) wearable hardware, a user interface on application (APP), and a cloud database are combined to build an artificial intelligence (AI) health-care platform.

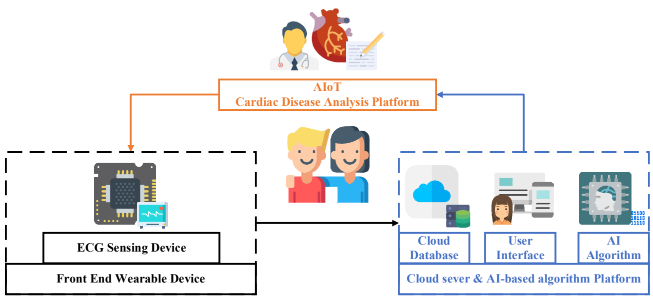



Fig 1. System block of ECG signal acquisition and application

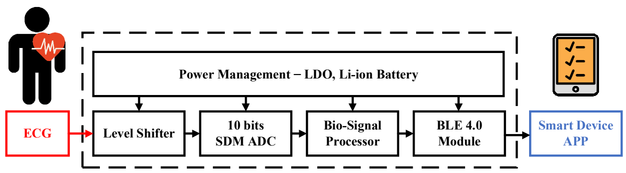



Fig 2. Front-end device block of the implemented ECG acquisition

## II. SYSTEM OVERVIEW

The artificial intelligence of things (AIoT) platform proposed in this study (Fig. 1) aims at analyzing real-time ECG signals to reduce the risks of severe arrhythmias. For real-time detection, low-power consumption, and long duration of use, a complete system structure, including a wearable front-end ECG sensing device, a user interface on smart device APP, a cloud database, and an AI-based algorithm for cardiac disease analysis, is presented and described in the following sections.

### *A. Wearable ECG monitoring device*

This study proposes a sensing hardware structure, as shown in Fig. 2, which includes an analog front-end circuit with low-power consumption, a commercial power management integrated circuit (IC), and a commercial Bluetooth module. The analog front-end circuit is a self-designed system on chip (SOC), which includes a 10-bit sigma–delta analog to digital converter, a level shifter and digital signal processing units. The commercial Bluetooth module applies Bluetooth Low Energy 4.0 to transmit the ECG signal collected by the front-end SOC to the APP instantly. The wearable ECG monitoring device with a single

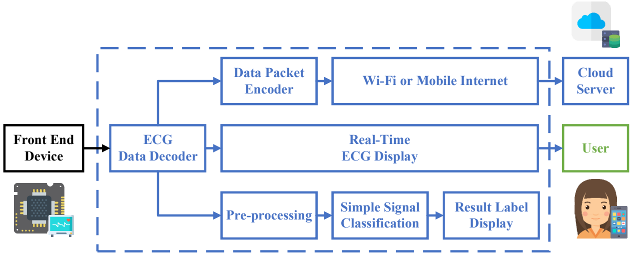



Fig 3. The smart device APP structure

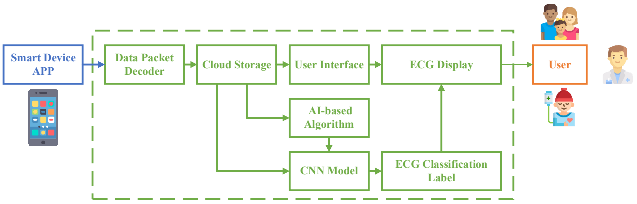



Fig 4. The cloud sever and database structure

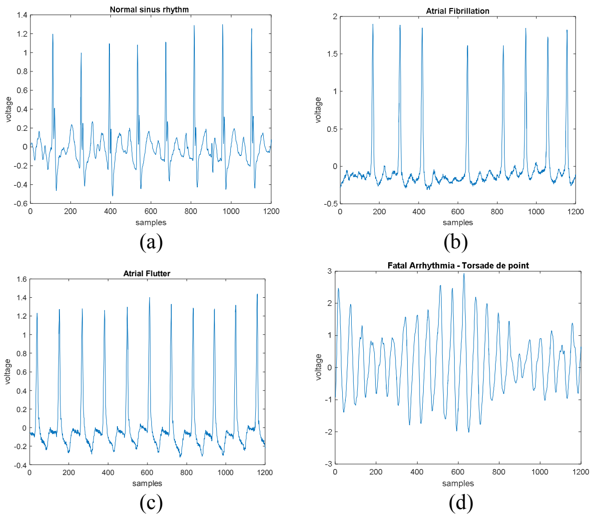



Fig 5. (a) normal ECG signal,(b) atrial fibrillation,(c) atrial flutter (d)ventricular fibrillation

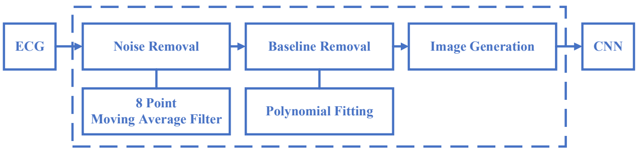



Fig 6. The pre-processing structure

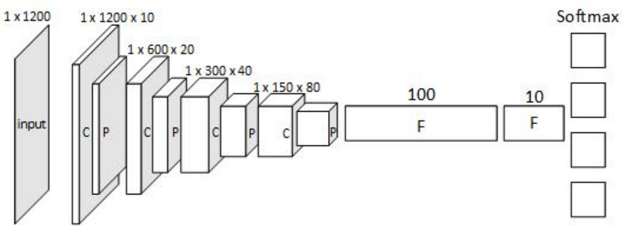



Fig 7. The neural network structure

lead is attached with two silver chloride wet electrodes on the chest, and it can be used up to 24 h under normal usage.

### B. *User interface on smart device APP*

A user interface on APP is also proposed, and the structure is shown in Fig. 3, which includes three main parts: an ECG-displaying function, an AI-based arrhythmia-analyzing function, and data-storing and data-transmitting function. The real-time ECG signal will be shown on the screen, and the AI algorithm is used to classify the user's ECG signal into different cardiac arrhythmias at the same time. By taking the computing power of modern mobile into account, the classification on smart devices shows only two categories: normal and abnormal. For further classification, the classification will be completed on the cloud server to obtain a more precise arrhythmia type from the user's ECG signal. The collected ECG data will not only be stored in local mobiles but also uploaded to the cloud database. For the sake of data safety and correctness, all the data will be encoded and added with time stamps.

### C. *Cloud server and database*

The structure of the cloud server and database is shown in Fig. 4. This server contains a big-data database, which includes three segments: data storage, web user interface, and AI-based algorithm for arrhythmia analysis. First, the data storage is in charge of receiving the data packages from the front-end smart devices, and the data packages are decoded as ECG signals. Furthermore, the ECG signals will be stored separately according to the measured objects and the measuring time stamps. Second, the web user interface provides doctors, patients, and patients' families a clear information platform. Doctors can diagnose patients' condition more specifically with the stored ECG data, and patients and their families can realize more about their daily ECG signal. Third, the AI-based algorithm can detect unusual signals from a large amount of data in several minutes. In general, a normal human produces approximately one hundred thousand heartbeats per day, and most of them are normal ECG signals; just a few are abnormal. Given this reason, doctors face a great challenge of diagnosing correctly with long-term ECG data. Through this cloud platform, the AI-based algorithm can quickly detect unusual signals, which will be displayed on the web user interface.

### D. *AI-based algorithm for arrhythmia classification*

The AI-based algorithm for arrhythmia classification has four categories: normal ECG, atrial fibrillation, atrial flutter, and ventricular fibrillation, as shown in Fig. 5. The structure of this algorithm has two segments: data pre-processing and CNN model. To make the CNN model have better feature learning, traditional ECG signal processing, such as time–frequency analysis, feature extraction, and R-peak and QRS-complex detection, are not carried out. The pre-processing structure proposed in this study includes three steps: noise removal, baseline removal, and image generation, as shown in Fig. 6. First, an 8-point moving average filter is applied for noise removal. The finite windows of moving average filter will take convolution with the signal. In addition, it will take an average of the output signal in the filter range to reduce the discrete-time noise and enhance the identification of the peak value. After many experiments and comparison, an 8-point moving average filter is selected.

Second, to solve baseline drift, polynomial fitting is performed for baseline removal. The concept is that a parametric curve is placed to approach the location of a known dataset, and then the fitting parametric signal is subtracted from the original signal to obtain a baseline-removed ECG data. Third, the design of image generation imitates how cardiologists read ECG signals. In general, cardiologists will consider when the abnormal ECG happened and provide sustained and non-sustained analysis on the following ECG. If three abnormal heartbeats are present or the unusual ECG signal lasts more than 30 s, cardiologists must note it as a special observation. Based on this concept, the pre-processed signal will transfer into images with sample rate of 1200 Hz (approximately 4.8 s). Finally, these images will be the training, validation, and testing data of the CNN model in the next stage.

This study takes a one-dimension CNN for feature extracting and classifying. To realize the CNN model by digital IC design in future work, the model cannot be too bulky to fulfill. The CNN model proposed in this study includes four convolutional layers and three fully connected layers. Each convolutional layer is followed by a leaky rectified linear unit (leaky ReLU) as active function. Leaky ReLU can not only have the benefits of traditional ReLU but also prevent several neurons from dead ReLU. In addition, part of the input data is negative, which may have some important features that must not be ignored. Given the above reasons, a leaky ReLU is selected as active function. Fig. 7 shows the structure of the neural network applied in this study. The model takes a max pooling with stride equal to 1 to extract more precise features. Furthermore, it also takes same padding to save the edge information from each input image. Next, the three fully connected layers make the number of output neurons from 100 to 10 and then shrink these 10 neurons to 4 categories as output. The filter order is set as 10 at the first convolutional layer and then doubles this order at each following layer. All the filter kernel orders are set as 180 to extract the desired features. The model chooses gradient descent as the optimizer. On top of that, the model sets the weight decay parameter, learning rate, and learning rate decay as 0.0001, 0.1, and 0.9 after every epoch, respectively. The ratios between training data, validation data, and test data are 8:1:1.

## III. EXPERIMENTAL RESULT

To verify this AIoT system, it is applied to the Ministry of Health and Welfare for clinical trials, which are carried out from patients in Tainan Hospital, Ministry of Health and Welfare. Each segment, such as the wearable ECG-sensing device, user interface on APP, cloud server, and AI-based algorithm for arrhythmia classification, will be tested in these trials.

### A. Wearable ECG-sensing device

Fig. 8(a) shows the front-end ECG-sensing device, which has a dimension of 84.55 mm × 39.38 mm × 18.31 mm. Fig. 8(b) shows a demonstration of how the ECG-sensing device is used. The ECG measurement is single lead with a 24 h duration.

### B. User interface on smart device APP

Fig. 9 shows the proposed user interface on APP. The upper part displays the raw data from the user's ECG signal, while the lower part displays the output results from the arrhythmia classification algorithm. Each ECG signal will be labeled as a normal ECG signal or an abnormal one.

(a) (b)

Fig 8. (a) The front-end sensing device (b) The actual ECG measurment

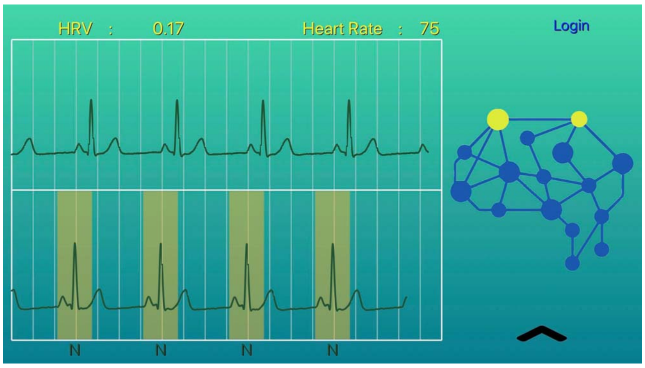
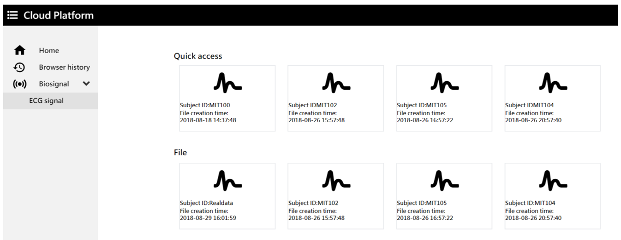



Fig 9. The proposed iOS APP screenshot




(a)


(b)

Fig 10. (a)&(b) The proposed WEB screenshot

### C. Cloud server and database

Fig. 10 (a) shows the web user interface, which can retrieve the user's historical ECG data, so that he/she can have further discussions with doctors. The web user interface is quite similar with the user interface on APP, as shown in Fig. 10(b). The upper and lower parts also display the ECG raw data and output results from the arrhythmia classification algorithm, respectively. Each ECG signal will be labeled as multiple types of ECG, such as different types of arrhythmias, which is slightly different from the user interface on APP.

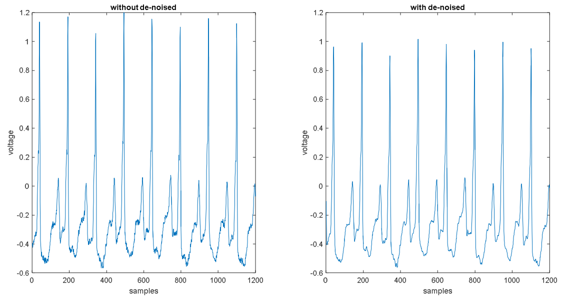



Fig 11. The result without(left)/with(right) noise removal

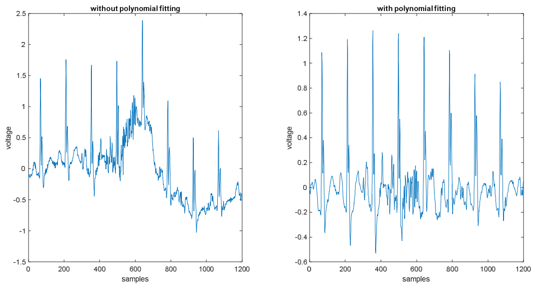



Fig 12. The result without(left)/with(right) baseline removal

### *D. AI-based algorithm for arrhythmia classification*

In order to have a suitable input dataset, several data pre-processing functions are necessary. First, the difference between the data with and without noise removal is shown in Fig. 11. It is realized by applying an 8-point moving average filter. Second, baseline removal is completed by polynomial fitting, and the result is shown in Fig. 12. This study proposes a one-dimension CNN. Considering the possibilities of realizing this model by digital IC design and the results after many experiments, the CNN model is suitably designed with four convolutional layers and three fully connected layers. Based on many tests, the weight decay parameter, learning rate, and learning rate decay parameter are set as 0.0001, 0.1, and 0.9 after every epoch, respectively. The proposed CNN model processes not only the data from clinical trials but also on the dataset from MIT-BIH [3]. The results are shown in Tables I and II. The average accuracies of the dataset from MIT-BIH and the data from clinical trials are 95.73% and 94.96%, respectively. Comparisons between this study and previous works are shown in Table III.

TABLE I. OPEN SOURCE DATABASE TESTING RESULT

| | NSR | Afib | Afl | FA | Accuracy |
|---|---|---|---|---|---|
| NSR | 272 | 9 | 0 | 0 | 96.69% |
| Afib | 15 | 371 | 3 | 0 | 95.37% |
| Afl | 9 | 1 | 69 | 1 | 93.24% |
| FA | 0 | 0 | 0 | 7 | 100% |

TABLE II. CLINICAL TRIAL DATABASE TESTING RESULT

| | NSR | Afib | Afl | FA | Accuracy |
|---|---|---|---|---|---|
| NSR | 9531 | 130 | 15 | 17 | 98.35% |
| Afib | 16 | 249 | 9 | 5 | 89.24% |
| Afl | 0 | 0 | 0 | 0 | - |
| FA | 0 | 0 | 0 | 0 | - |

TABLE III. PERFORMANCE COMPARSION

| | This work | 2017[4] | 2016[5] | 2016[6] |
|---|---|---|---|---|
| Classification target | NSR, Afib, Afl, FA | NSR, Afib, Afl, Vfib | NSR, Afib, Afl, Vfib | Afib, Afl, Vfib |
| Model | CNN | CNN | Rotation forest | Decision tree |
| Accuracy | Clinical trial testing is 94.96% MIT-BIH testing is 95.73% | 94.9% | 98.37% | 96.3% |
| Testing Database | Clinical trials MIT-BIH | Open source | Open source | Open source |

## IV. CONCLUSION

This study proposes a complete AIoT system platform, which is an integrated health-care system, including a hardware, a software, and a cloud database, and is expected to enhance health. The AI-based algorithm for arrhythmia classification, which takes professional cardiologist's advice as reference, has a simpler data pre-processing progress and a suitable identification pattern compared with other algorithms. However, to overcome the problems from individual differences and enhance the model's tolerance, more data are needed from different clinical individuals, which can be used to train the model and further modify the pre-processing function. In addition, this work takes single-lead ECG as the measurement, which means it cannot analyze some types of arrhythmia. In the future, this work hopes to improve the model as simple as possible to realize the AI-based algorithms on chip. The prospect is to reach a real AIoT-based system for cardiac disease detection and broadcast health care to every individual.

## ACKNOWLEDGMENTS

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